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著者	Mizuki Takeda, Yasuhisa Hirata, Takahiro Katayama, Yasuhide Mizuta, Atsushi Koujina
journal or publication title	IEEE Robotics and Automation Letters
volume	3
number	4
page range	3011-3018
year	2018-06-21
URL	http://hdl.handle.net/10097/00130853

doi: 10.1109/LRA.2018.2849551

State Estimation Using the CoG Candidates for Sit-to-Stand Support System User

Mizuki Takeda[1], Yasuhisa Hirata[1],
Takahiro Katayama[2], Yasuhide Mizuta[2], and Atsushi Koujina[2]

***Abstract*— Various support systems have been developed to support elderly people, and the demand for indoor support system has increased. It is important to support not only walking but also to support sit-to-stand and stand-to-sit motions. We develop a support system for indoor use that depends on the user's state such as sitting or standing. Although it is useful for assistive devices to be able to select how to support users based on sensor data, it is difficult to utilize many expensive and sophisticated sensors for accurate estimation of the user's state. In this study, we propose an estimation method of the user's state utilizing a few inexpensive and simple sensors. Firstly, we propose the method to calculate the CoG candidates using a human link model. The CoG candidates are then used to develop a state estimation method for sit-to-stand motion; this motion consists of three contiguous states: sitting, rising, and standing. A Support Vector Machine (SVM) is used to estimate the user state and the methods were experimentally validated using the developed assistive robot. The experimental results show that the estimations are correct except in the vicinities of state transitions. The average state transition time errors are 0.175 s and 0.145 s for sit-to-rise and rise-to-stand, respectively. Since sit-to-stand motion is contiguous, the user's state is ambiguous and can be both states at the boundaries. Therefore, the accuracy of the state estimation is reasonable.**

I. Introduction

Due to population aging, the demand for assistive indoor support systems has increased and various systems have been developed. It is important to support not only walking but also sit-to-stand and stand-to-sit motions. Although many people need simpler support systems such as canes, walkers, and handrails, more advanced systems using robot technology could offer better support and prevent falling accidents.

There are several types of assistive robots, such as lift type [1], [2], cane type [3] or walker type [4]. Cane type systems are useful for indoors environment owing to their size, but they can't sustain the user's weight during sit-to-stand motion. Lift type support systems can make up for a user's lack of strength and keep the user's posture during sit-to-stand motion [1]. Since this motion is important, systems which can not only support but also analyze the motion have been developed [2]. However, since these assistive robots are focused on sit-to-stand motion, they can't support walking. By contrast, although walker type support systems are steadier than canes and can support walking, they are a little larger. Some researchers are developing walker type support systems which can support both walking and sit-to-stand and stand-to-sit motions [5], [6]. Walker type support systems which have an armrest can sustain the user's state with a larger area than push cart types.

It is important to provide appropriate support depending on the situation, and real-time user's state estimation is needed. However, it is difficult to obtain the user's precise state. Thus several types of user information have studied extensively.

There has been interest on ground reaction forces to make wearable sensors such as shoe-type [7]. Such sensors can be used anywhere unlike force plates. Moreover, accelerometers have been added to wearable sensors, followed by combining the data [7], [8].

Muscle information such as muscle potential is also used to analyze human motion [9]. Some researchers also study vision based estimation [10], [11].

The center of gravity (CoG) is also useful. Wearable accelerometers are frequently used to measure or estimate the CoG. For example, inertial measurement units (IMUs) are set on the human body where influence the acceleration of CoG [12], [13], [14]. Human link models are also used to estimate human motion. We can calculate the CoG position from the link positions of the model. Some researchers use position sensors or distance sensors such as motion capture systems, laser range finders (LRFs) or position sensitive detector sensors to measure the information of the links [5], [15]. IMUs or force sensors are also used to obtain the link parameters [14], [16].

These methods need many sophisticated sensors, or sensors which must be set on users. Therefore, it's difficult for such systems to be implemented in general households or institutions. Thus, we aim to use a few simple sensors for estimating users' state. The objective of this study is the development of a robot with a few sensors which can support not only walking, but also sit-to-stand and stand-to-sit motion; we also propose a support system based on the user's state estimation using the robot. Firstly, for state estimation, we focused on the CoG. Since it is physically meaningful about the human body, it can be implemented to various systems. Since human posture directly influences the CoG, it can be used to estimate the user's state and it could be used for detection of anomalies and intents.

In [17], we proposed a method to calculate candidates of CoG and the appropriate combination of sensors to reduce the range of CoG candidates which was obtained from the experimental results. It is expected that the user's state can be estimated by using narrow CoG candidates. In [18], we

[1]M. Takeda, and Y. Hirata are with Department of Robotics, Tohoku University, 6-6-01 Aramaki-Aoba, Aoba-ku, Sendai 980-8579, Japan. {m.takeda, hirata}@srd.mech.tohoku.ac.jp

[2]T. Katayama, Y. Mizuta, and A. Koujina are with RT.WORKS CO., LTD., 1-10-26, Nakamichi, Higashinari-ku, Osaka 537-0025, Japan.

developed the armrest type assistive robot. Supporting both hands and elbows is effective during especially sit-to-stand motion in the context of safety. The user's sit-to-stand motion can be assisted by moving the armrest when the user leans to the armrest. If we can estimate whether the user is only sitting or the user intends to stand, we can start to move the armrest at the timing of start standing.

In this study, we set the sensors to the developed robot based on the knowledge of sensor arrangement, which is obtained from [17]. Then, we propose a new calculation method of CoG candidates, which requires less sensors than [17]. The user's feet are considered not to move largely during the sit-to-stand motion. Thus, by using the range of the ankle joint position, some groups of the CoG candidates can be calculated per frame. We also propose a method to estimate the user's state using the CoG candidates. We focus on sit-to-stand motion, and consider that the motion is consist of three contiguous states: sitting, rising, and standing. A Support Vector Machine (SVM) is used for the state estimation. Finally, we validate the proposed method by experiments using the assistive robot.

II. Development of the Support System

The sensor arrangement, which we adopted from the results of [17] is discussed in section II-A. The previous calculation method of the CoG candidates of [17] is explained in section II-B. The developed assistive robot is explained in section II-C.

A. Sensor Arrangement of Developed Assistive Robot for Estimating User State

Firstly, we consider the human link model as shown in Fig. 1, same as [17]. We can calculate the CoG position by positions and mass ratios of the links [19], [20] as shown in Fig. 2. If we start to use an assistive robot, we can measure the user's height or limbs length before using. Therefore, we assume that the lengths of human link model are known.

Some parameters remain unknown when we use lesser sensors than required to calculate the model and the CoG position becomes underspecified. Using the unknown parameters' ranges, we can calculate the candidates of CoG position. By properly selecting and placing sensors, we can make the CoG candidates' range narrow enough for state estimation.

In [17], various patterns of measurement sets as shown in Fig. 3 were proposed, and the calculation method was validated. Sensors that are generally used on assistive machines are selected. Black lines of Fig. 3 represent the human link model. Black squares represent the links' angles which are measurable by using sensors. Black points are the measured points' positions such as joints. These positions are defined as relative positions to the assistive robot as shown as the coordinate system in Fig. 1. The coordinate system is attached to the back of the robot. The sets of a number and an alphabet are the names of measurements sets. The numbers denote the quantities of the unknown parameters of the measurements sets. For example, measurements set

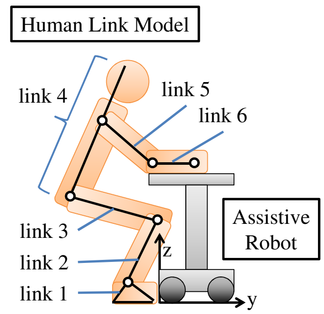


Fig. 1. Human Link Model and Assistive Robot with Coordinate Frame

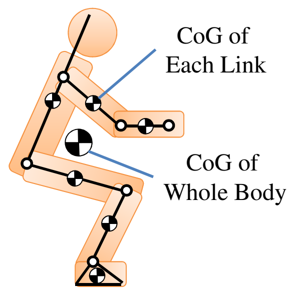


Fig. 2. Human Link Model and the CoG (Center of Gravity)

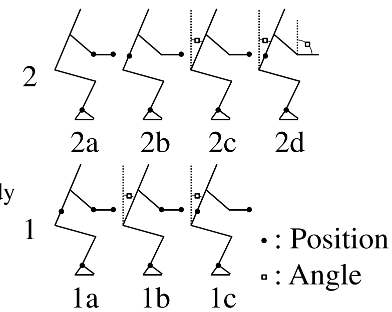


Fig. 3. Measurements Sets

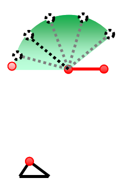
1a needs one more parameter to calculate the human link model and the accurate CoG position.

The experiments were conducted to validate the CoG candidates calculation method in [17]. The maximum errors of the CoG candidates relative to the actual CoG were discussed. When the user is standing or close to standing phase, the maximum errors of **1a**, **1c**, and **2b** are about 100 mm, which are considerably small. On the other hand, in the case of **1b**, **2a**, and **2c**, the maximum errors are 200 - 300 mm, which seems large. These results suggest that the body link position is especially important. In the case of **1a**, the maximum errors are also about 100 mm when the user is rising. And the maximum errors are smaller than 200 mm except when the user is fully sitting. These CoG candidates errors are small enough to consider the movement of the CoG position since the CoG path is longer than the errors. The experimental results show that the CoG candidates' range is especially narrow for measurements set **1a**. It is expected that the narrow CoG candidates are better for state estimation. The measurements set **1a** consists of:

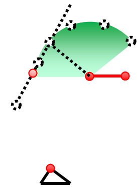
- Positions of wrists: touch sensors of grippers
- Positions of elbows: touch sensors of armrests
- Positions of ankles: distance sensors
- A Position of one point of body link: a distance sensor

B. Fundamental CoG Candidates Calculation Method

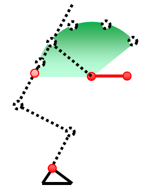
In this section, we will discuss the CoG candidates calculation method, which was proposed in [17]. When using the measurements sets **1a**, positions of wrist, elbow, ankle joint, and one point of body link can be measured. Thus, the



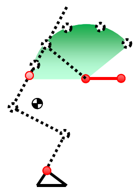
(a) All Candidates of Shoulder Joint



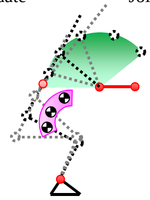
(b) Corresponding Hip Joint Candidate



(c) Corresponding Knee Joint Candidate



(d) Corresponding CoG Candidate



(e) All CoG Candidates of Whole Human Body

Fig. 4. Calculation of CoG Candidates (**1a**) [17]

forearm and foot links positions can be identified however, the others cannot be identified.

Since the upper arm link's length is known, the candidates of the shoulder joint can be calculated by considering the elbow joint's rotation range, as shown in Fig. 4(a). The shoulder joint candidates are calculated discretely. Focusing on one shoulder joint candidate, the corresponding candidate of hip joint can be calculated as shown in Fig. 4(b). Black dash lines are the focused candidates of links. From the rotation ranges of hip, knee, and ankle, the corresponding knee joint candidate can be determined uniquely, as shown in Fig. 4(c). One set of candidates of all links and joints positions is calculated from the above-mentioned procedure. Thus, the corresponding CoG candidate can be calculate as shown in Fig. 4(d). All candidates of the CoG position can be calculated by repeating the procedure above as shown in Fig. 4(e).

C. Developed Assistive Robot

We developed an assistive robot in [18]. The robot is shown in Fig. 5. The robot was designed based on the general activities of daily living such as sit-to-stand motion. The specifications of the robot are shown in TABLE I. The robot is designed to be able to pass a typical toilet door of general households in Japan. Supporting sit-to-stand and stand-to-sit motion is important especially for indoor support. In the context of safety, supporting not only hands but also elbows is effective during walking, and especially sit-to-stand motion. Therefore, the developed robot is armrest type, and the armrest can move up-and-down by a linear actuator. It can support the user's sit-to-stand motion by moving the armrest when the user leans on the armrest. This armrest can lift a weight of 40 kg, and it's enough to assist elderly people to stand. From the simulation results of joints' load, it is designed to be able to lift 75% of the user's upper body weight. The armrest can move lowest to highest about 4 s. It is suitable for elderly people to standing, and the speed of the linear actuator is adjustable for each person. The way of support is designed on the basis of the analyses of physical therapists' sit-to-stand assist motions.

Fig. 5. Developed Assistive Robot (Left: Lowest Armrest, Right: Highest Armrest)

TABLE I
SPECIFICATIONS OF DEVELOPED ASSISTIVE ROBOT

	Value	Unit
Height	77 - 103	cm
Armrest Height	71 - 97	cm
Length	50	cm
Width of Armrest	46	cm
Width of Robot Body	54	cm
Armrest Moving Time	4	s
Armrest Weight Capacity	40	kg

TABLE II
SPECIFICATIONS OF DISTANCE SENSOR

	Value	Unit
Measuring Distance Range	4 - 50	cm
Response Time	40	ms
Price	$<$10	US$

The measurements sets named **1a**, **1b**, and **2a** can be used for the developed assistive robot since the robot is armrest type. From the results of [17], the measurements set **1a** is adopted because the CoG candidates range is narrow. It is expected that the narrow CoG candidates are better for state estimation.

It is known whether the user's wrists and elbows are on the grippers and armrests, respectively, because the robot has touch sensors on these parts. The height of armrest can determine from the displacement of the linear actuator. The wrist and elbow positions are defined as the center of each joint. The positions are determined by using the height of armrest and the thickness of the forearm link.

We set a GP2Y0E03 distance sensor made by SHARP CORPORATION on the back of the armrest. The specifications of the sensor are shown in TABLE II. The armrest moves during sit-to-stand motion, and the sensor can measure the distance between the body link and armrest. The position is determined by using the thickness of the body link as same as the wrist and elbow joints. Thus, using only a few simple sensors, all required data of measurements set **1a**, except for the ankle joints positions, was obtained. The ankle positions can be measured if we use expensive sensors such as LRFs. However, it is too expensive and difficult to use in general households. We now propose a new calculation method of the CoG candidates that does not need ankles positions.

III. The CoG Candidates Calculation and State Estimation

The new method to calculate the CoG candidates without using ankles positions is presented here, along with the state estimation method using the CoG candidates.

Firstly, we propose the new CoG candidates calculation method using a small number of sensors in section III-A. The range of the ankle position is used to calculate the groups of CoG candidates. We validate the method by the experiment in section III-B.

In section III-C, we propose a method to estimate the user's state using the CoG candidates. We consider that the sit-to-stand motion consists of three contiguous states; sitting, rising, and standing. If sitting and rising states can be discerned, the height of the armrest can be controlled. The robot should not move during sitting and rising for safety. However, when the user intends to walk, it should be able to move. We can control these if we can estimate the states of the sit-to-stand motion.

A. CoG Candidates Calculation Method Using the Ranges of Ankles Positions

When people undergo sit-to-stand motion, the ankle positions don't change since their feet sustain their whole body weight. When using the developed robot, the users' arms sustain some weight because of the armrest. However, most of whole body weight is also sustained by their feet.

We set the ranges of ankle positions as $0-350$ mm from the assistive robot. The range is set by considering the relative position of a user and the assistive robot, size of the assistive robot, and parameters of the human link model. Feet don't move from the ground during sit-to-stand motion, so the z-coordinate of ankle joint doesn't change during the motion. We set the origin on the ground just below the edge of the assistive robot as shown in Fig. 1, and the ankle range is represented as y = $0-350$ mm. We consider eight groups of ankle candidates as y = 0, -50, -100, -150, -200, -250, -300, and -350 mm. Then we can calculate users' data which is represented in Fig. 6 by using the assumption and the sensors noted above. Black points are the measured points' positions. Black lines mean that the positions of the links are determined uniquely. Grey dash lines and circles are the candidate positions of links and joints, respectively. Only three representative foot links are shown in Fig. 6 due to the visibility.

We can calculate eight groups of CoG candidates per frame from the data represented in Fig. 6 by using measurements set **1a**. Firstly, we focus on one ankle joint candidate and then consider the range of elbow joint. The candidates of the shoulder joint can be calculated as shown in Fig. 7(a) since the length of the upper arm link is known. Black dash lines and joints are the focused ones of the candidate

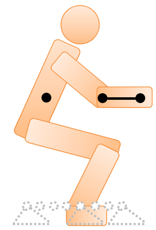
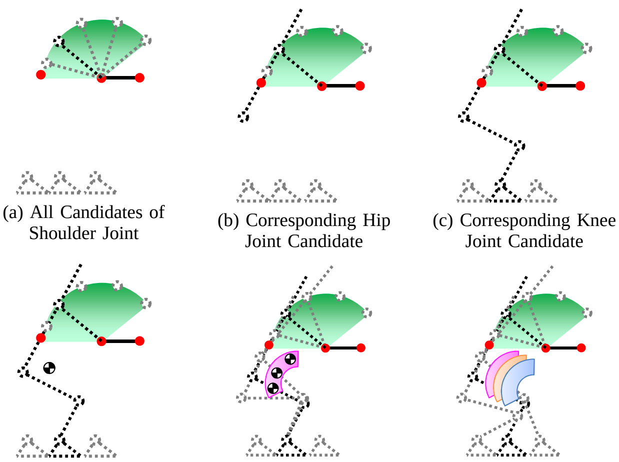


Fig. 6. Users' Data Which Can Be Calculated by Using the Developed Assistive Robot (Black Points: Position Measured Points, Black Lines: Position Determined Links, and Grey Dash Circles: Candidate Positions of Joints, Grey Dash Lines: Representative Candidate Links)



(a) All Candidates of Shoulder Joint
(b) Corresponding Hip Joint Candidate
(c) Corresponding Knee Joint Candidate
(d) CoG Candidates Corresponding to the Focused Candidates Set
(e) All CoG Candidates Corresponding to the Focused Ankle Candidate
(f) All Groups of CoG Candidates Corresponding to the Ankle Candidates

Fig. 7. Calculation Procedure of CoG Candidates

links and joints, respectively. Since the body link's length is also known, the position of each hip joint candidate which corresponds to shoulder joint candidate. We focus on one candidate set of shoulder and hip joint as shown Fig. 7(b). The corresponding knee joint candidate is calculated as shown in Fig. 7(c). Candidate positions of all links can be calculated from the positions of joints, links, and their candidates. Thus we can calculate the corresponding CoG candidate position as shown in Fig. 7(d). By repeating this procedure, all the candidates of CoG position corresponding to the ankle candidate can be calculated as shown in Fig. 7(e). Therefore, we can calculate eight groups of CoG candidates by repeating the procedure above for all ankle candidates, as shown in Fig. 7(f).

B. Validation Experiments of the Proposed CoG Candidates Calculation Method

We conducted an experiment to validate the proposed CoG candidates calculation method. Firstly, the participant is sitting on a chair with his forearms on the armrest of the robot. When the participant finishes leaning his body, the armrest moves up from lowest to highest. The participant raises his body according to the rise of the armrest. Finally the participant stands. The robot doesn't move except for the armrest during the sit-to-stand motion for safety. We measured the user's sit-to-stand motion by using a motion capture system. The actual CoG position can be calculated by adding the value of the unknown parameters of the measurement set from the motion capture data. The CoG candidate can be compared with the actual CoG. We used six Kestrel Digital Cameras and two Osprey Digital Cameras, made by Motional Analysis Corporation. We used dedicated software, Cortex, for data processing.

The calculation results of CoG candidates are shown in Fig. 8 - Fig. 10. In Fig. 8, the calculated eight groups of CoG candidates are represented as pink points. And the black lines represent the human link model measured by using the motion capture system. The black rhombus point is the actual CoG. Fig. 9 shows enlarged views of the CoG candidates. Each group of CoG candidates are drawn with different color in Fig. 9. Pink, cyan, green, red, brown, grey, blue, and orange points represent the CoG candidates which are calculated by assuming that the position of the ankle joints are 0, -50, -100, -150, -200, -250, -300, -350 mm, respectively. Enlarged views of the parts of the CoG candidates are shown in Fig. 10. Large circles, triangles, and squares are the representative candidates in the cases of 0, -200, and -350 mm, respectively. They are calculated by using larger intervals of discrete values of the elbow joint's rotation angle.

As shown in Fig. 8 - Fig. 10, the CoG candidates are calculated; their accuracies are also similar to the previous work. We confirmed that the method is effective for the calculation of CoG candidates when the positions of the ankles are unknown; this is largely unchanged from the case using the ankle positions.

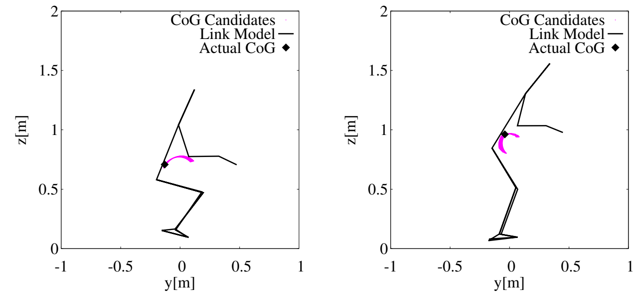
C. State Estimation Method

It is important to use the CoG candidates for state estimation since they have physical significance. For example, we can estimate whether the user is likely to fall by the location of the projected point of the CoG against the base of support; this is likely to be implemented in various systems.

We focus on sit-to-stand motion, and consider that the motion consists of three contiguous states; **sitting**, **rising**, and **standing**. The users of the assistive robot basically conduct the sit-to-stand motion in the same way as described in section III-B. When the user is only sitting or leaning on the robot and the armrest is lowest, the user is sitting. When the armrest of the assistive robot is moving upward, the user is rising. When the armrest is highest and user is leaning or straight, the user is standing.

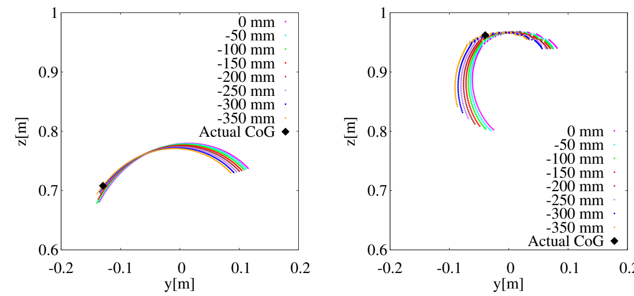
SVM is adopted to estimate the user's state since it allows us to set features manually. It can be trained for each user since the training time is not so long. We set geometric features of the CoG candidates as the features of SVM, which are,

- Average value of y-coordinate of the CoG candidates
- Average value of z-coordinate of the CoG candidates
- Value of integral of the group of the CoG candidates
- Maximum value of y-coordinate of the CoG candidates
- Maximum value of z-coordinate of the CoG candidates
- Minimum value of y-coordinate of the CoG candidates



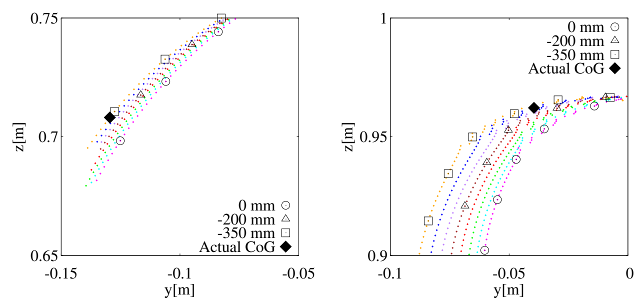
(a) Sitting (b) Standing

Fig. 8. 8 Groups of CoG Candidates with Human Link Model



(a) Sitting (b) Standing

Fig. 9. Enlarged Views of 8 Groups of CoG Candidates (Y-Coordinate of Ankle Joint Is Assumed $0-350$ mm)



(a) Sitting (b) Standing

Fig. 10. Parts of the CoG Candidates (Representative Candidates Are Emphasized by Symbols)

- Minimum value of z-coordinate of the CoG candidates

as shown in Fig. 11. The values of integral are calculated by considering pixels as shown in Fig. 12. The size of one pixel is $5 \times 5\ \mathrm{mm}^2$. The absolute value of the integral means little since the group of CoG candidates draw a curve line with no thickness. However, the relative value of the integral which is calculated using same definition is effective for comparing the size of each group of the CoG candidates. Therefore, the integral value of the CoG candidates group can be used for state estimation as one of the features of SVM. The position and the form of the group of the CoG candidates can be figured out from the features described above. Normalized values of features are inputted to SVM. The RBF kernel is used for SVM. We confirmed that the all features are significant on the classification.

As we described in section III-A, eight groups of CoG candidates can be calculated per frame. Thus, eight estimated states were obtained per frame. If the all estimates are the

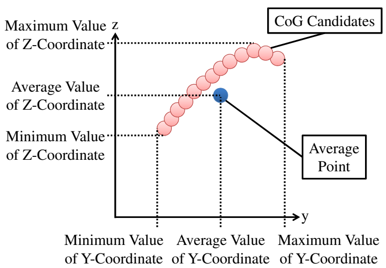


Fig. 11. Utilized Features on the State Estimation

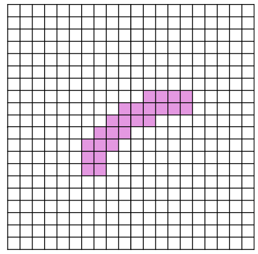


Fig. 12. Pixels for Calculation of Integral Value of the CoG Candidates

(a) Sitting (b) Rising (c) Standing

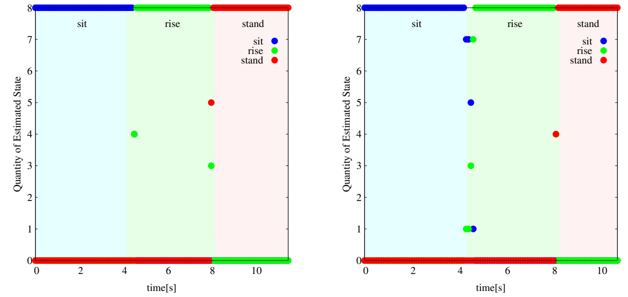
Fig. 13. Sit-to-Stand Motion (Participant B)

same in a frame, the estimate of the frame is the same. However, if estimates are different in a frame, the majority is adopted. If more than one state is dominant, we adopt one which is same as the previous frame.

IV. State Estimation Experiments Using Simple Sensors Which Are Set on the Assistive Machine

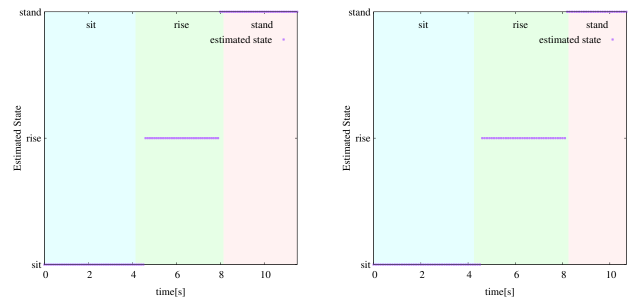
We conducted the experiments to validate the method which we described in section III. Twenty participants conducted sit-to-stand motions using the developed assistive robot 11 times such as shown in Fig. 13. They conducted the same sit-to-stand motion as described in section III-B. Firstly, the participants sat on a chair and put their hands and elbows on the grippers and armrests of the assistive robot. Then they conducted the sit-to-stand motion using the robot. The participants are both genders, 21 - 31 years old, 164 - 189 cm tall, and weighing 52 - 97 kg. None had any physical disability. Informed consent was obtained from all participants before the experiments.

We calculated the candidates of CoG based on the method described in section III-A. The length of each participant's links were measured and used. The thickness of bodies varied with different clothes. Since body thickness is not measured before each use, it is difficult to account for this value accurately. Therefore, the thicknesses of body and forearm links of participant A are used for all participants. Training data comprised 10 data of the measured sit-to-stand motion for each participant. The participants' states of the other data were estimated based on the method described in section III-C. As SVM software, LIBSVM [21] is used. We shot the videos of the experiments, and determined the actual participants' states visually, and compared the results of estimation.



(a) Participant A (b) Participant B

Fig. 14. Time Variation of the Quantities of Groups Which Show Each State as the Estimation Result



(a) Participant A (b) Participant B

Fig. 15. Time Variation of Estimated State (Participants A and B)

Participants A and B's time variations of the quantities of the groups which show each state as the estimation result are shown in Fig. 14. Blue, green, and red points are the quantities of the CoG candidates groups which show sitting, rising, and standing as the estimation result, respectively. Blue, green, and pink areas are the phases when user is sitting, rising, and standing, respectively. For example, from 0 s to 4.4 s of participant A, the quantity of groups which show **sitting** as the state estimation result is 8, with **rising** and **standing** are 0. It means that all CoG candidates groups show the same state as the estimation result in the term. At vicinities of state transition, some groups show the different state estimation results such as at 8 s of participant A. By adopting majority, the estimated state become more accurate than using only one CoG candidates group.

The participants' time variations of the estimated state are shown in Fig. 15, and accuracies of the state estimations are shown in TABLE III and TABLE IV, respectively. Purple points in Fig. 15 are the estimated state. Purple point located at the bottom, center, and top indicates that the estimated state is sitting, rising, standing, respectively. The results indicate that the estimation is almost correct. The estimation errors occur only near the boundaries between states. In other words, the errors indicate that the estimates of the transitions start either a little early or a little late. TABLE III shows the quantities of the frames of the estimated states compared to actual states of participant A. For example, the participant A's rise was estimated as sitting in 4 frames. Since each frame is 0.1 s, the error is 0.4 s. This error occurs only at a state transition; thus, the result means that the state transition estimation at sit-to-rise was delayed by 0.4 s.

TABLE III

STATE ESTIMATION ACCURACY (PARTICIPANT A)

Quantities of Frames		Estimated State Sit	Rise	Stand
Actual State	Sit	42	0	0
	Rise	4	34	2
	Stand	0	0	34

TABLE IV

STATE ESTIMATION ACCURACY (PARTICIPANT B)

Quantities of Frames		Estimated State Sit	Rise	Stand
Actual State	Sit	44	0	0
	Rise	2	36	1
	Stand	0	0	25

Estimation errors of state transition time is shown in TABLE V. The positive numbers mean late errors of the transition time and negative ones mean early errors.

Since sit-to-stand motion is contiguous, the user's state can appear to be simultaneously in two states near the boundary; the boundaries were visually determined. We can assist users even if there is a little error of state transition time by adjusting the timing. Thus it causes no problem if we estimate the transitions a little early or late. From TABLE V, we know that the state transition time errors are considerably short. We confirmed that the proposed state estimation method is effective when using the sensors, which are actually set on the assistive robot.

As shown in TABLE V, almost all participants' results have same trend. The beginning of the rising, the armrest height, and user's posture are little different from sitting. By the end of rising, they are almost identical to standing. In the case of the participant I, the state transition time error of rise-to-stand is late. It may be caused by the difference of posture. The users often lean forward when rising and stand straight after standing. So the timing of upper body movement may affect the result.

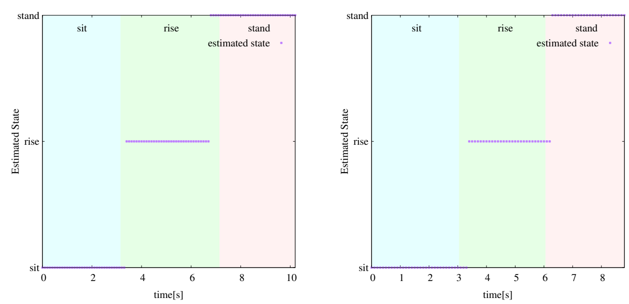
Time variation of the estimated state of participants E and I are shown in Fig. 16. It shows that the state estimates are correct except in the vicinity of the boundaries between states. All participants' results have same trend, which means that there are no failures except in the vicinity of the state transitions. In the case of the participant E, time error of rise-to-stand state transition is a little large in contrast to the result of participant A. As described above, participant I's state transition time error of rise-to-stand is late, unlike the others'. It is likely that the posture of this participant affected the result. The user's state is ambiguous at the boundaries, and the time error is short enough to allow compensation by adjusting the support function of the robot.

From these results, it is clear that we can estimate the assistive robot users' state by using only a few simple sensors. The users' states are estimated using only 10 training data, and no SVM hyperparameters such as regularization

TABLE V

STATE TRANSITION TIME ERROR

Participant Number	State Transition Time Error (s) Sit-to-Rise	Rise-to-Stand
A	$+0.4$	-0.2
B	$+0.2$	-0.1
C	± 0	-0.2
D	$+0.1$	-0.2
E	$+0.2$	-0.4
F	$+0.2$	-0.2
G	$+0.2$	-0.2
H	$+0.2$	-0.1
I	$+0.3$	$+0.2$
J	$+0.1$	-0.2
K	$+0.1$	-0.1
L	$+0.2$	-0.1
M	$+0.1$	-0.2
N	$+0.2$	-0.1
O	± 0	-0.2
P	$+0.2$	-0.2
Q	$+0.3$	-0.1
R	$+0.2$	-0.1
S	$+0.1$	-0.1
T	$+0.2$	-0.1
Average	$+0.175$	-0.145



(a) Participant E (b) Participant I

Fig. 16. Time Variation of Estimated State (Participants E and I)

constant C are optimized. It suggests that preparation is little enough for using the robot. This method can be applied for anomaly detection and acquisition of useful data since the CoG position candidates can be obtained. This information can be used to select the timing of support functions such as moving the armrest. The CoG is physically meaningful and the relationship between the user's CoG and the robot position is used for the proposed state estimation method. Therefore, the method can be implemented in other systems with few changes. In this study, the experiments were conducted with young participants. Similar results are expected with elderly people who actually need such assistive robots because there are no fundamental physical differences. We plan to conduct these experiments with the cooperation of elderly people to validate our method.

V. CONCLUSION

In this study, we present a developed assistive robot which can support a user's movements for indoor support, and we proposed an estimation method of the user's state from the CoG candidates by using a reduced number of sensors.

In order to assist a user with sit-to-stand motion, the assistive robot needed to be able to sustain the user's weight over a large area during sit-to-stand motion. The development of an armrest type assistive robot followed, which can sustain some of the user's weight by the armrest; it can support sit-to-stand motion by moving the armrest higher. The user's state estimation is important to enable variation of the support methods of the system. The armrest can move at the beginning of the motion since the state estimation determines whether the user intends to stand; this decision can be used to keep the robot's wheels immobilized during sit-to-stand motion. We equipped the robot with fewer sensors than required to calculate the CoG position. Subsequently, we proposed the CoG candidates calculation method by considering the ranges of the unknown parameters of the human model. This was followed by the proposed state estimation method by using the CoG candidates. Finally, we experimentally validated the proposed method using a few simple sensors on the robot.

Though the estimation results were analyzed offline, this estimation method can be implemented in real-time without large changes. Although the learning time of the SVM is a little long, it can be finished before using the assistive robot and thus it causes no problem. The CoG candidates calculation is O(8N), and the estimation time of SVM is less than 0.005 s. In this study, training data comprised 10 data of the measured motion. We intend to explore necessary amount of data to reduce the preparation before using and the user's strain. Training data can be collected while using the assitive robot. Therefore, by renewing the SVM training data while using, the state estimation will be able to get better day by day.

Future work could involve implementation of the proposed method for other motions, such as stand-to-sit and walking. The method can also be applied to anomaly detection. The CoG candidates can also be used to decide the timing of the changing support function by detection of the user's intent. By considering the relationship between the CoG candidates and the actual CoG, it is expected that the CoG candidates can become narrower, furthermore, the actual CoG position can be estimated. Finally, we intend to conduct similar experiments with elderly people, who actually need assistive robots.

Ethics Statement

The proposed system and experiments using the developed assistive robot were reviewed and approved by the ethics board of the Foundation for Yokohama Rehabilitation Services. All experiments were conducted after obtaining informed consent from all participants.

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